

Degenerate Nonlinear Programming with Unbounded Lagrange Multiplier Sets

Applications to Mathematical Programs with
Equilibrium Constraints

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Nonlinear Program (NLP)

For $f, g, h \in C^2(R^n)$

$$\begin{array}{ll} \text{minimize}_{x \in \mathbf{R}^n} & f(x) \\ \text{subject to} & h_i(x) = 0 \quad i = 1, \dots, r \\ & g_j(x) \leq 0 \quad j = 1, \dots, m \end{array}$$

Inequality Constraints Only

$$\begin{array}{ll} \text{minimize}_{x \in \mathbf{R}^n} & f(x) \\ \text{subject to} & g_j(x) \leq 0 \quad j = 1, \dots, m \end{array}$$

The results can be extended for equality constraints as long as $\nabla_x h_i(x)$,
 $i = 1, \dots, r$ are linearly independent. Degeneracy: linearly dependent
gradients of active constraints.

KKT conditions

The active set at a feasible $x \in \mathbb{R}^n$:

$$\mathcal{A}(x) = \{j | 1 \leq j \leq m, g_j(x) = 0\}$$

Stationary point of NLP: A point x for which there exists $\lambda \geq 0$ such that

$$\nabla_x f(x) + \sum_{j \in \mathcal{A}(x)} \lambda_j \nabla_x g_j(x) = 0$$

The Lagrangian: $\mathcal{L}(x, \lambda) = f(x) + \sum_{j=1}^m \lambda_j g_j(x) = f(x) + \lambda^T g(x)$.

Complementarity formulation for stationary point:

$$\emptyset \neq \mathcal{M}(x) = \{\lambda \in \mathbb{R}^m \mid \lambda \geq 0, \nabla_x \mathcal{L}(x, \lambda) = 0, g(z) \leq 0, (\lambda)^T g(z) = 0\}$$

KKT theorem: under certain constraint qualification conditions, the solution x^* of the NLP is a stationary point of the NLP.

Mangasarian-Fromovitz Constraint Qualification

- Mangasarian Fromovitz CQ (MFCQ): The tangent cone to the feasible set $\mathcal{T}(x^*)$ has a nonempty interior at x^* or
$$\exists p \in R^n ; \text{ such that } \nabla_x g_j(x^*)^T p < 0, j \in \mathcal{A}(x^*).$$
- MFCQ accommodates constraint degeneracy: linearly dependent active gradients.
- MFCQ holds \Leftrightarrow The set $\mathcal{M}(x^*)$ of the multipliers satisfying KKT is bounded.
- The critical cone:
$$\mathcal{C} = \{u \in R^n \mid \nabla_x g_j(x^*)^T u \leq 0, j \in \mathcal{A}(x^*), \nabla_x f(x^*)^T u \leq 0\}$$
- If MFCQ does not hold then
$$\mathcal{T}(x, u) = \{u \in R^n, |g_j(x) + \nabla_x g_j(x)^T u \leq 0, j = 1, \dots, m\}$$
 may be empty x arbitrarily close to x^* . **Problem for SQP!**

Second-order optimality conditions (SOC)

Necessary SOC (Ioffe): In presence of MFCQ, $\forall u \in \mathcal{C}(x^*)$,

$$\max_{\lambda \in \mathcal{M}(x^*)} u^T \mathcal{L}_{xx}(x^*, \lambda) u = \max_{\lambda \in \mathcal{M}(x^*)} u^T \nabla_{xx}^2(f + \lambda^T g)(x^*) u \geq 0$$

Sufficient SOC: MFCQ and $\exists \tilde{\sigma} > 0$ such that $\forall u \in \mathcal{C}(x^*)$

$$\max_{\lambda \in \mathcal{M}(x^*)} u^T \mathcal{L}_{xx}(x^*, \lambda) u = \max_{\lambda \in \mathcal{M}(x^*)} u^T \nabla_{xx}^2(f + \lambda^T g)(x^*) u \geq \tilde{\sigma} \|u\|^2.$$

Sufficient SOC imply Quadratic Growth:

$$\max \{f(x) - f(x^*), g_1(x), g_2(x), \dots, g_m(x)\} \geq \sigma \|x - x^*\|^2 > 0$$

L_∞ SQP algorithm near x^*

SQP: Sequential Quadratic Programming.

1. Set $k = 0$, choose x^0 .
2. Compute d^k from

$$\begin{aligned} \text{minimize} \quad & \nabla f(x^k)^T d + \frac{1}{2} d^T d \\ & g_j(x^k) + \nabla g_j(x^k)^T d \leq 0, \quad j = 1, \dots, m. \end{aligned}$$

3. Choose α^k using Armijo for the nondifferentiable merit function $\phi(x) = f(x) + c_\phi \max\{g_0(x), g_1(x), \dots, g_m(x), 0\}$, $c_\phi > 0$, and set $x^{(k+1)} = x^k + \alpha^k d^k$.
4. Set $k = k + 1$ and return to Step 2.

Main Theorem

Suppose x^* satisfies MFCQ and the Quadratic Growth Condition

$$\max \{f(x) - f(x^*), g_1(x), g_2(x), \dots, g_m(x)\} \geq \sigma \|x - x^*\|^2 > 0$$

Then x^* is an isolated stationary point of the NLP. If x^0 is sufficiently close to x^* , with x^k generated by the steepest descent algorithm with an L_∞ penalty function with sufficiently large c_ϕ .

- x^* is an unconstrained minimum of $\phi(x^*)$.
- $x^k \rightarrow x^*$ R-linearly.
- $\phi(x^k) \rightarrow \phi(x^*)$ Q-linearly.

Unbounded Lagrange Multiplier Set Approach

Assumptions

$$\min_x f(x) \quad \text{subject to } g_i(x) \leq 0, \quad i = 1, 2, \dots, m.$$

- The Lagrange Multiplier set is not empty (but may be unbounded).
- The quadratic growth condition holds
$$\max \{f(x) - f(x^*), g_1(x), g_2(x), \dots, g_m(x)\} \geq \sigma \|x - x^*\|^2$$
- f, g are twice continuously differentiable.

The modified nonlinear program

$$\min_{x, \zeta} f(x) + c\zeta \quad \text{subject to } g_i(x) \leq \zeta, \quad i = 1, 2, \dots, m, \quad \zeta \geq 0.$$

For $c > c_\zeta$ at $(x^*, 0)$ we have

- The Lagrange multiplier set is nonempty and bounded (MFCCQ).
- The quadratic growth condition is satisfied.
- The data of the problem are twice differentiable.

All preceding results apply, including the linear convergence result!

The effect of the modification

- Lagrange Multiplier set of the original problem: $\mathcal{M}(x^*)$.
- Lagrange Multiplier set of the modified problem: $\mathcal{M}^c(x^*, 0)$.
 $\mu^c \in \mathcal{M}^c(x^*, 0) \Rightarrow \|\mu^c\| = c.$
- Reduced Lagrange Multiplier set.
$$\begin{aligned}\mathcal{M}_r^c(x^*) &= \{\mu \in \mathbb{R}^m \mid \exists \mu_{m+1} \in \mathbb{R}, \\ &\quad \text{such that } (\mu, \mu_{m+1}) \in \mathcal{M}^c((x^*, 0))\}.\end{aligned}$$
- $\mathcal{M}_r^c(x^*) \subset \mathcal{M}(x^*)$. The penalty term $c\zeta$ has the effect of preserving only the multipliers $\mu \in \mathcal{M}(x^*)$ with $\|\mu\|_1 \leq c$!

Robinson's Example

$$\begin{array}{llll}\min_x & f(x) & = & (x - 1)^2 \\ \text{subject to} & g_1(x) & = & (x - 1)^6 \sin \frac{1}{x-1} \leq 0. \\ & g_2(x) & = & -(x - 1)^6 \sin \frac{1}{x-1} \leq 0.\end{array}$$

Since the local minima are $1 + \frac{1}{k\pi}$, which accumulate at 1, a nonlinear optimization algorithm is likely to stop before reaching 1, no matter how close to 1 it is initialized!

Results from the direct application of NLP

Solver Type	$ x - x^* $	Iterations	Message
LANCELOT	3.09e-12	60	Step got too small
LOQO	3.18e-01	149	Primal dual infeasible
SNOPT	3.18e-01	1	Optimal solution found
FilterSQP	3.18e-01	13	Optimal solution found
LINF	3.18e-01	13	Step got too small

Except LANCELOT, all algorithms stop at $1 - \frac{1}{\pi}$ (penalty).

For $y = (x, \zeta)$

$$\begin{array}{llll} \min_{x, \zeta} & f^c(y) & = & (x - 1)^2 + \zeta \\ \text{subject to} & g_1^c(y) & = & (x - 1)^6 \sin \frac{1}{x-1} - \zeta \leq 0 \\ & g_2^c(y) & = & -(x - 1)^6 \sin \frac{1}{x-1} - \zeta \leq 0 \\ & g_3^c(y) & = & -\zeta \leq 0, \end{array}$$

All Lagrange multipliers μ^* satisfy $\|\mu^*\|_1 = c = 1$.

Modified nonlinear program

Results for the modified problem

Solver Type	$ x - x^* $	Iterations	Message
LANCELOT	2.18e-12	297	Step got too small
LOQO	2.9e-2	1000	Iteration limit
SNOPT	5.6e-12	10	No improvement
FilterSQP	7.45 e-13	42	Optimal solution found
LINF	0	39	Optimal solution found

Linear convergence of the merit function was observed for LINF.

Mathematical Programs with Equilibrium

Constraints, MPPEC

$$\begin{array}{llll} \text{minimize}_x & f(x) & & \\ \text{subject to} & g(x) & \leq 0 & \\ & h(x) & = 0 & \\ & F_{k1}(x) & \geq 0 & k = 1 \dots K \\ & F_{k2}(x) & \geq 0 & k = 1 \dots K \\ \text{Compl. constr.} & F_{k1}(x)F_{k2}(x) & = 0 & k = 1 \dots K \\ \text{The Lagrangian: } & \mathcal{L}(x, \Gamma, \lambda, \mu) & = f(x) - F(x)\Gamma + g(x)\lambda + h(x)\mu & \end{array}$$

NLP_{*I*}

$$\begin{array}{ll}\text{minimize}_x & f(x) \\ \text{subject to} & g(x) \leq 0 \\ & h(x) = 0 \\ & F_I(x) = 0 \\ & F_{I^c}(x) \geq 0\end{array}$$

There is at least one index set I at a solution x^* such that

$$\begin{aligned}I = I(x^*) &= \{(k, i) \in \{1 \dots K\} \times \{1, 2\} \mid F_{ki}(x^*) = 0, \\ \text{and } \forall k \exists i : (k, i) &\in I(x^*)\}.\end{aligned}$$

Stationary Points of NLP_I

Assume:

- $F_{k1}(x^*) + F_{k2}(x^*) > 0, \forall k \in \{1 \dots K\}$ (strict complementarity).
- NLP_I satisfies strict MFCCQ at $x = x^*$ for $I = I(x^*)$ (MFCCQ and uniqueness of multipliers).

Then (Scheel and Scholtes, 2000)

- \exists unique Γ, λ, μ such that

$$\nabla_x \mathcal{L}(x^*, \Gamma, \lambda, \mu) = 0, g(x^*) \leq 0, (\lambda)^T g(x^*) = 0$$

- $$\Gamma \geq 0, F(x^*) \geq 0, F(x^*) * \Gamma = 0$$
- For every critical direction d of NLP_I we must have
 $d^T \nabla_{xx}^2 L(x^*, \Gamma, \lambda, \mu) d \geq 0.$

Properties of the original MPPEC

- If, in addition, for every nonzero critical direction d of NLP_I we have $d^T \nabla_{xx}^2 L(x^*, \Gamma, \lambda, \mu)d > 0$, then, for some $\sigma > 0$

$$\max \left\{ f(x) - f(x^*), \|g^+(x)\|, \|h(x)\|, \|F_I(x)\| \right\} \geq \sigma \|x - x^*\|^2 > 0.$$

- Since $F_{k1}(x^*) + F_{k2}(x^*) > 0$, then for some $\sigma_1 > 0$,

$$\begin{aligned} \max & \quad \{f(x) - f(x^*), \|g^+(x)\|, \|h(x)\|, \|F^+(x)\|, \|F_{11}(x)F_{12}(x)\|, \\ & \|F_{21}(x)F_{22}(x)\|, \dots, \|F_{K1}(x)F_{K2}(x)\| \} \geq \sigma_1 \|x - x^*\|^2 > 0. \end{aligned}$$

- The original MPPEC formulated as a nonlinear program has a nonempty Lagrange multiplier set and satisfies the quadratic growth constraint.

Numerical Experiments with SNOPT

The elastic mode of SNOPT implements a similar approach.

Problem	Var-Con-CC	Value	Status	Feval	Elastic
gnash14	21-13-1	-0.17904	Optimal	27	Yes
gnash15	21-13-1	-354.699	Optimal	12	None
gnash16	21-13-1	-241.441	Optimal	7	None
gnash17	21-13-1	-90.7491	Optimal	9	None
gne	16-17-10	0	Optimal	10	Yes
pack-rig1-8	89-76-1	0.721818	Optimal	15	None
pack-rig1-16	401-326-1	0.742102	Optimal	21	None
pack-rig1-32	1697-1354-1	0.751564	Optimal	19	None

Results Obtained with Minos

Problem	Var-Con-CC	Value	Status	Feval	Infeas
gnash14	21-13-1	-0.17904	Optimal	80	0.0
gnash15	21-13-1	-354.699	Infeasible	236	7.1E0
gnash16	21-13-1	-241.441	Infeasible	272	1.0E1
gnash17	21-13-1	-90.7491	Infeasible	439	5.3E0
gne	16-17-10	0	Infeasible	259	2.6E1
pack-rig1-8	89-76-1	0.721818	Optimal	220	0.0E0
pack-rig1-16	401-326-1	0.742102	Optimal	1460	0.0E0

Conclusions

- The Quadratic Growth condition and MFCQ imply isolated stationary points.
- Nonlinear Programs with nonempty, though possibly unbounded, Lagrange multiplier sets can be transformed in Nonlinear Programs with the same solution set that satisfy MFCQ and thus present isolated stationary points.
- Mathematical Programs with Equilibrium Constraints may create difficulties for some SQP algorithms by generating infeasible subproblems.
- Nevertheless, the use of a penalty approach (elastic mode) can accommodate these cases in an efficient manner.